A Decomposition Software Package for the Decomposition of Long-term Multi-channel Electromyographic Signals

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Abstract- **The analysis of intramuscular EMG signals is based on the decomposition of the signals into basic units. Existing decomposition software only supports short registration periods or single-channel recordings of signals of constant muscle effort. In this paper, we present the decomposition software EMG-LODEC (ElectroMyoGram LOng-term DEComposition) that is especially designed for multi-channel long-term recordings of signals of slight muscle movements. Based on experiments on simulated and recorded EMG signals, our software is capable of providing reliable decompositions with satisfying accuracy. EMG-LODEC is suitable for the study of motor-unit discharge patterns and recruitment order in healthy subjects and patients.**

I. INTRODUCTION

Long-term analysis of neuro-muscular systems, such as the analysis of the development of chronic muscle pain, requires intramuscular electromyogram (EMG) recordings of several minutes to several hours duration. The analysis of the measured signals is based on the decomposition of the signals into basic signal units called motor-unit action potentials (MUAPs). Existing decomposition software only support short registration periods (about 10 seconds) and often is limited to single channel recordings of signals of constant muscle effort recorded by needle electrodes. A well-written review of several decomposition algorithms is given in [3].

Most automated EMG analysis techniques are developed for clinical short decomposition, where recorded EMG signals of constant muscle effort guarantee small shape-changes and regular activation patterns [2], [6], [7]. Most algorithms require only single-channel measurements. An algorithm that uses multi-channel measurements is De Luca's algorithm [5], which is based on measurements with the quadrifillar-needle electrode during non-dynamic muscle conditions. However, to analyze work-related musculoskeletal disorders [4], the study of muscle fibre groups, named motor-units (MUs), under dynamic conditions has become of great interest in neurology and ergonomics. For this reason we considered algorithms, which are based on discrete Wavelet coefficients, clustering, supervised classification, and template matching.

In this paper the concept of the decomposition software is outlined. Furthermore we present evaluation results for both simulated and real EMG signals.

II. METHODOLOGY

A. Decomposition Concept

EMG signal decomposition is usually divided in to several processing stages. First, the EMG signal is bandpass filtered. After this filtering, the EMG signal is divided into so called *inactive* segments with low activity and *active* segments containing MUAPs. The beginning and the end of the active segments are detected by thresholding based on the estimated signal noise power. Only the active segments serve as a basis for the following classification. In Fig. 1 the classification concept for active EMG segments is shown.

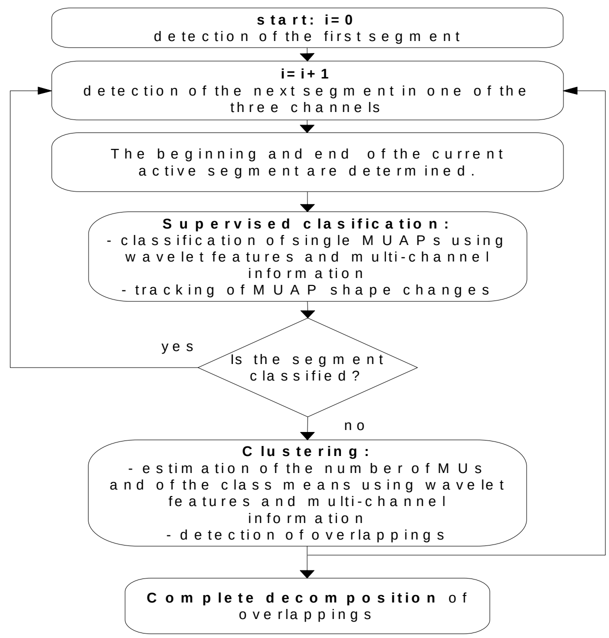

Fig. 1. Classification concept for EMG segments.

To estimate the number of classes, to determine the templates, i.e. class-mean signals, and to detect MUAP overlap, a wavelet based hierarchical cluster analysis is applied first, which is based on a modified single linkage-clustering concept [9].

Then each active segment is compared to the set of templates and classified by the supervised classifier. The supervised classifier is based on the discriminant wavelet coefficients, multi-channel signal information, and the weighted averaging method [11], in order to track action-potential shape changes. Finally, the last stage is the decomposition phase, in which we separate overlapping action potentials into their units using class-mean signals in order to obtain the complete activation pattern.

B. Segmentation

The goal of the segmentation is to divide the EMG signals into inactive and active segments. After bandpass-filtering the EMG signal, the signal noise power of the inactive segments is estimated. The estimation of the bandpass filtered and discrete EMG signals $s_{EMG}[k]$ is done automatically. The positions of the inactive segments are

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Abstract

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unknown. The estimated signal power is computed according to

$$\sigma_i^2 = \frac{1}{L_R} \sum_{k=i}^{i+L_R-1} s_{EMG}^2[k], \tag{1}$$

where L_R is the length of a window $(L_R \in Z)$. Assuming that for the minimum of σ_i^2 the window borders on an inactive segment, the following equation for the noise power is used

$$\hat{\sigma}_n^2 = \min_i \sigma_i^2, \tag{2}$$

where σ_n^2 is the noise power and σ_i^2 is the signal power of the i^{th} segment. With the estimated noise power and the signal samples, the active segments can be determined (Fig. 2).

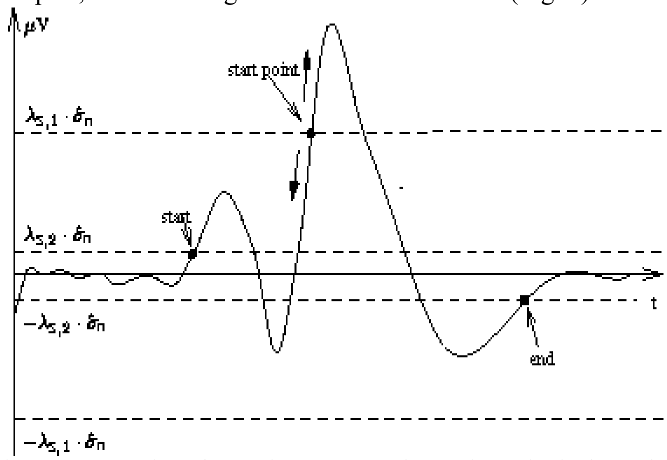

Fig. 2. Segmentation of an active segment. The starting point is detected before the program determines the start and end of the active segments. $\lambda_{S,1}$ and $\lambda_{S,2}$ define the start and end points of the active segments and are specified by the user.

C. Classification

The aim of the classification stage is to estimate the number of classes, to determine the templates, and to detect overlaps. The classification of active segments is one of the most demanding parts of the decomposition algorithm due to a number of factors such as the low SNR (signal to noise ratio), the MUAP changes due to muscle fatigue and electrode or muscle movement. Furthermore, the MUAP waveforms of different MUs, which can be very similar, the small distances between the class-means, and the alignment error of time-triggered waveforms caused by time offsets, make the classification difficult. This is shown in Fig. 3, where time triggered MUAPs of five different MUs are shown.

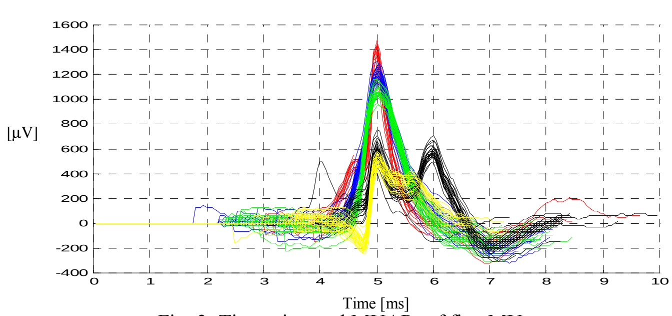

Fig. 3. Time triggered MUAPs of five MUs.

Wavelet coefficients

For the clustering and the supervised classification of active segments we are using extracted wavelet coefficients. The use of wavelet coefficients from selected frequency bands can improve the clustering performance, as shown in [10]. Given the definition of the multiresolution analysis in [8], the wavelet coefficients $F_c[m,n]$ of a finite energy signal $c(t)$ are defined as

$$F_c[m,n] = \langle \psi_{m,n}(t), c(t) \rangle = \int_{-\infty}^{\infty} \psi_{m,n}(t) c(t) dt \tag{3}$$

with

$$\psi_{m,n}(t) = 2^{\frac{m}{2}} \psi(2^{-m} t - n), \tag{4}$$

where $\psi(t)$ denotes the wavelet basis function, n the shift parameter and m the scaling number. Using the Fourier transform of $\psi_{m,n}(t)$ the wavelet coefficients can be described by

$$F_c[m,n] = \frac{2^{\frac{m}{2}}}{2\pi} \int_{-\infty}^{\infty} C(\omega) \psi^*(2^m \omega) e^{j2^m n\omega} d\omega, \tag{5}$$

where $C(\omega)$ is the Fourier transform of c(t) and $\psi(\omega)$ is the Fourier transform of $\psi(t)$. Defining $e(t)$ as the difference signal between $f(t)$ and $g(t)=f(t-\tau)$, with $\tau \in$ [-T/2,T/2] and using the Parseval theorem, we can write

$$\|e(t)\| = \|f(t) - g(t)\| = \sqrt{\sum_m \sum_n \left| F_f[m,n] - F_g[m,n] \right|^2} \tag{6}$$

This means that most of the energy of e(t), depending on the Fourier transform, is concentrated in the highest frequency band of the signal. Thus, the wavelet coefficients of the highest band should be avoided for classification. For physiological reasons the power density spectrum of MUAP waveforms is mainly concentrated in the frequency range between 200 Hz and 2 kHz. Therefore, we extract the wavelet coefficients for the classification from this frequency range, which improves the classification performance. Outliers can be more easily detected, clusters can be better separated, and the SNR can be increased, according to this wavelet –based distance measure.

Another advantage of using the wavelet-based measure is that the number of features can be significantly reduced compared to a minimum distance classifier using all time samples [9]. This reduction in features improves the accuracy and the processing time compare to previously published classification methods. For the classification, the features, which distinguish the different classes best, are of great importance. As a quality parameter, the Fisher criterion is used

$$r_{Fisher,l} = \sum_{i=1}^{J-1} \sum_{j=i+1}^{J} \frac{(\mu_{i,l} - \mu_{j,l})^2}{\sigma_{i,l}^2 + \sigma_{j,l}^2}, \tag{7}$$

where $\mu_{j,l}$ is the mean and $\sigma_{j,l}^2$ the variance of the l^{th} features of the j^{th} classes and J is the number of classes. The criterion

parameters became high, if the clusters among themselves are well separated.

Clustering of detected MUAPs

Several different clustering techniques were tested for EMG segment classification [2]. Simulations have shown that the single-linkage nearest-neighbor cluster method, which is a hierarchical clustering algorithm, is best suited for EMG clustering [9]. The method extracts wavelet features from certain frequency bands to calculate the distance between the segments. In the following we describe the modified single-linkage algorithm that we used.

The single-linkage algorithm permits a simple graph-theoretical interpretation, namely the minimum spanning tree (MST) method [11]. This is illustrated in Fig. 4, where the space of wavelet coefficients is represented. Each segment is denoted by a dot. The lines between the dots are the distances between two connected segments. Given the distances between all segments, and by removing those lines whose distances are greater than a given threshold, groups of clusters, i.e. MUs, are formed and outliers can be found. The distances between the clusters and the largest distances within the cluster influence the grouping of the clusters.

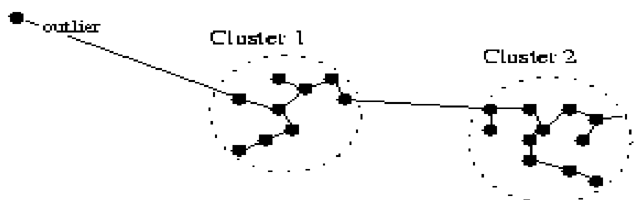

Fig. 4. A minimum spanning tree.

The distance d_{ij}^{SL} between two clusters (G_i, G_j) can be expressed by

$$d_{ij}^{SL} = \min d_{p,g}(p \in G_i, q \in G_j), \qquad (8)$$

where p is an element from cluster i (G_i) and q an element from cluster j (G_j). The Euclidean distances between the MST vectors are stored in a distances matrix. The size of the matrix, i.e. the number of segments considered in the clustering part, depends on the activity of the EMG signal and changes during the decomposition. To detect MUAP overlaps or outliers, which influence the estimation of the number of classes, we use the definition of the distance measure. The commonly used criterion for an active segment belonging to a MU is that at least five other segments belong to the same MU, i.e. have a distance smaller than a threshold. In contrast to other algorithms, we use this criterion to detect overlap and outliers *before* grouping clusters. With the MUAP waveforms of the different clusters, the class-means were determined.

Supervised classification of MUAPs

To classify non-overlapping MUAPs, to follow MUAP shape changes, and to reduce the calculation complexity and the misclassification rate, we use supervised classification techniques. The supervised classifier is based on the most discriminant wavelet coefficients, which are determined by the Fisher criterion (7), and the clustering results. Due to muscle fatigue and electrode or muscle movements, the MUAP shapes change over time. To overcome this problem the class means are adapted during the decomposition. We used weighted averaging techniques to adapt the class-means

$$\underline{\hat{x}}_{i+1,j} = \underline{\hat{x}}_{i,j} - \beta(\underline{\hat{x}}_{i,j} - \underline{x}_{i,j}) \qquad (9)$$

$$= \underline{x}_{0,j}(1-\beta)^{i+1} - \beta\sum_{k=0}^{i}\underline{x}_{k,j}(1-\beta)^{i-k}, \qquad (10)$$

where $\underline{\hat{x}}_{i+1,j}$ denotes the class-mean of the time point i+1 of the jth MU, $\underline{x}_{i,j}$ the last classified signal and β the forgetting factor. The adaptation is completed when:

$$D_2 \geq \sqrt{\alpha} D_1, \qquad (11)$$

where D_2 is the Euclidean distance to the second nearest template, and D_1 the Euclidean distance to the nearest template.

D. Complete decomposition

Finally, non-classified segments, i.e. detected outliers, e.g. segments containing overlapping action potentials, are decomposed into their units using class-mean signals. For the exact determination of the activation patterns, the decomposition of those segments is based on the classification results, such as the number of classes, the prototype waveform of a class, and the variance within a class.

III. RESULTS

To evaluate our decomposition algorithms we tested it both with clinically measured and with artificially generated multi-channel long-term EMG signals.

A. Evaluation using simulated EMG signals

To create artificial intramuscular EMG signals, we used Farina’s model for the generation of synthetic intramuscular EMG signals [1]. The simulated EMG signal provides known features that serve as a basis for comparison. In this study, the performance of our algorithm was evaluated with 4 simulated EMG signals with 3 channels. Each signal was 10 seconds long and corrupted with Gausian white noise at the level of 20 dB SNR. The sampling frequency was 10 kHz. Additional characteristics of the simulated signals are given in Table I.

TABLE I

CHARACTERISTIC FEATURES OF THE ARTIFICIALLY INTRAMUSCULAR EMG SIGNAL

EMG	M	N	f_i	$N_{\%S}$	$N_{S,max}$	α_{max}	v_{W1}	v_{S2}
1	4	390	5, 6,5,6	0	0	0	0.02	0.05
2	5	342	8,9,7,8,9	10	2	0.1	0.01	0.01
3	5	244	12,9,5,10,9	10	3	0.6	0.01	0.01
4	8	553	12,9,12,10.9,5,5	10	2	0.4	0.01	0.01

where M denotes the number of MUs, N the total number of MUAPs, f_i the firing frequencies of the M MUs, $N_{\%,S}$ the percentage of superimposed MUAPs, $N_{S,max}$ the maximum number of MUAPs in a superposition, $\alpha_{\%max}$

the maximum degree of superposition, v_{W1} the random shape variability and v_{S2} the random scale variability [1].

To evaluate the performance of our software package, the 4 artificially generated signals were also decomposed with the software package MAPQuest [2].

B. Evaluation with measured long-term EMG signals

Measured EMG signals from 6 healthy subjects during different computer tasks, such as tapping, tracking, and number inputting were used. Each task had a duration of 10 minutes. To make measurements under dynamic muscle conditions we used fine wire electrodes (stainless steel with Teflon insulation, diameter 80 μm). When the muscle is moving this procedure is much less painful compared to common techniques, and the baseline levels of the EMG signals are less influenced by the muscle movements. Six channels of intramuscular EMG were picked up from the trapezius muscle. The recording was carried out at a sampling rate of 20 kHz.

IV. DISCUSSION

The decomposition of the 4 artificially generated signals with our software package leads in the mean to 96.48 % correctly detected, 0.65 % wrongly detected, and 3.53 % non-detected MUAPs. Compared to the results with MAPQuest we achieved a better performance. The recognition rates depend on the signal quality. The EMG signal 4 had high activity, 553 segments, and MUAPs with small energy, which influenced the results of the correct recognition rate and the rate of non-detected MUAPs. In Table II, the results for the 4 artificially generated EMG signals are given.

TABLE II
ACHIEVED DECOMPOSITION ACCURACY WITH ARTIFICIALLY GENERATED EMG SIGNALS

EMG	Percentage of correctly detected MUAPs		Percentage of wrongly detected MUAPs		Percentage of non-detected MUAPs	
	EMG-LODEC	**MAPQuest***	**EMG-LODEC**	**MAPQuest***	**EMG-LODEC**	**MAPQuest***
1	98.5 %	100 %	0.8 %	1.53 %	1.5 %	0 %
2	100 %	99.1 %	0 %	1.17 %	0 %	0.9 %
3	95.5 %	89.6 %	0.4 %	5.2 %	4.5 %	10.4 %
4	91.9 %	82.9 %	1.4 %	14.8 %	8.1 %	17.2 %
Mean	96.5 %	92.9 %	0.6%	5.7 %	3.5%	7.1 %
Std	3.6 %	8.2 %	0.6%	6.4 %	3.6%	8.2 %

*Each channel is separately decomposed and the mean of the results of the three channels are calculated and shown.

The decomposition of the 6 measured multi-channel long-term recordings leads to the following conclusion. Our decomposition algorithm was capable of detecting and tracking the long-term motor unit activity of those signals with a high degree of accuracy. MUAPs' shape changes could be observed over time and the program was capable of tracking most of them. The analysis of the 10 minutes measured EMG signals takes between 20 to 60 minutes depending on the activity of the signals.

The results of the decomposition seem to be reliable, but a quantitative analysis still needs to be done.

V. CONCLUSION

We have developed a decomposition concept, which allows a relatively fast and accurate analysis of multi-channel long-term recordings. Both simulated and observed EMG signals were used to test our technique. The performance of this technique was very good in terms of achievable accuracy. Based on the decomposition concept, a decomposition software package (EMG-LODEC) [9] has been written, which suits for the study of motor unit discharge patterns and recruitment order in both healthy and ailing subjects.

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